

**AFRL-SN-RS-TR-2001-243**  
**Final Technical Report**  
**November 2001**



# **SPACE-TIME ADAPTIVE PROCESSING (STAP) PERFORMANCE IN NON-HOMOGENEOUS RADAR CLUTTER**

**ARCON Corporation**

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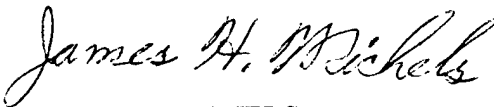
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**20020117 011**

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REPORT DOCUMENTATION PAGE			Form Approved OMB No. 0704-0188	
<small>Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503.</small>				
1. AGENCY USE ONLY (Leave blank)		2. REPORT DATE NOVEMBER 2001		3. REPORT TYPE AND DATES COVERED Final Dec 00 - Aug 01
4. TITLE AND SUBTITLE SPACE-TIME ADAPTIVE PROCESSING (STAP) PERFORMANCE IN NON-HOMOGENEOUS RADAR CLUTTER			5. FUNDING NUMBERS C - F30602-00-C-0231 PE - 61102F PR - 230R TA - SN WU - P2	
6. AUTHOR(S) Muralidhar Rangaswamy				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) ARCON Corporation 260 Bear Hill Road Waltham Massachusetts 02451			8. PERFORMING ORGANIZATION REPORT NUMBER  N/A	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Air Force Research Laboratory/SNRT 26 Electronic Parkway Rome New York 13441-4514			10. SPONSORING/MONITORING AGENCY REPORT NUMBER  AFRL-SN-RS-TR-2001-243	
11. SUPPLEMENTARY NOTES Air Force Research Laboratory Project Engineer: James H. Michels/SNRT/(315) 330-4432				
12a. DISTRIBUTION AVAILABILITY STATEMENT APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.			12b. DISTRIBUTION CODE	
13. ABSTRACT (Maximum 200 words) Abstract report addresses the statistical analysis of the non-homogeneity detector (NHD) for non-Gaussian interference scenarios. An important issue in STAP is that of homogeneity of training data. Non-homogeneity of the training data has a deleterious effect on STAP performance in that undernull clutter significantly degrades detection and false alarm characteristics. Previous work in this area has proposed the use of non-homogeneity detector based on a generalized inner product (GIP). The unsuitability of the GIP based test for non-Gaussian interference scenarios is noted. We present a new non-homogeneity detector for non-Gaussian interference scenarios which can be modeled by a spherically invariant random process (SIRP). Our work includes a statistical analysis of the NHD for non-Gaussian interference taking into account the fact that finite sample support is used for covariance estimation. In particular, exact theoretical expressions for the NHD test statistic PDF and the mean of a related test statistic are derived. We also note that the related test statistic admits a remarkably simple stochastic representation as a ratio of an F-distributed random variable and a beta-distributed loss factor. Based on this development, a formal goodness-of-fit test is presented. Performance analysis is carried out using simulated and measured data from the MCARM Program.				
14. SUBJECT TERMS Non-Homogeneity Detector, NHD, STAP Non-Homogeneous Clutter, Generalized Inner Product, Non-Gaussian Clutter, Space-Time Adaptive Processing			15. NUMBER OF PAGES 24	
			16. PRICE CODE	
17. SECURITY CLASSIFICATION OF REPORT  UNCLASSIFIED	18. SECURITY CLASSIFICATION OF THIS PAGE  UNCLASSIFIED	19. SECURITY CLASSIFICATION OF ABSTRACT  UNCLASSIFIED	20. LIMITATION OF ABSTRACT  UL	

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# Chapter 1

## Acknowledgments

The author is thankful to Drs. J.H. Michels and B. Himed of the U.S. Air Force Research Laboratory, for their insightful comments and stimulating technical discussions. The author is grateful to Drs. B. Himed, J.H. Michels, and for their collaborative efforts on several conference and journal publications.

# Chapter 2

## Executive Summary

This research effort represents our investigation on the problem of statistical analysis of the non-homogeneity detector for non-Gaussian interference scenarios. An important issue in STAP is that of homogeneity of training data. Non-homogeneity of the training data has a deleterious effect on STAP performance in that undernulled clutter significantly degrades detection and false alarm characteristics. Previous work in this area has proposed the use of a non-homogeneity detector (NHD) based on a generalized inner product (GIP). The unsuitability of the GIP based test for non-Gaussian interference scenarios is noted. We present a new nonhomogeneity detector for non-Gaussian interference scenarios which can be modeled by a spherically invariant random process (SIRP). Our work includes a statistical analysis of the NHD for non-Gaussian interference taking into account the fact that finite sample support is used for covariance estimation. In particular, exact theoretical expressions for the NHD test statistic PDF and the mean of a related test statistic are derived. We also note that the related test statistic admits a remarkably simple stochastic representation as a ratio of an F-distributed random variable and a beta-distributed loss factor. Based on this development, a formal goodness-of-fit test is presented. Performance analysis is carried out using simulated and measured data from the MCARM Program.

## Chapter 3

# Statistical Analysis of the Nonhomogeneity Detector for Non-Gaussian Interference Backgrounds

### 3.1 Introduction

An important issue in space-time adaptive processing (STAP) for radar target detection is the formation and inversion of the covariance matrix underlying the clutter/ interference. In practice, the unknown interference covariance matrix is estimated from a set of independent identically distributed (iid) target-free training data which is assumed to be representative of the interference statistics in a cell under test. Frequently, the training data is subject to contamination by discrete scatterers or interfering targets. In either event, the training data becomes nonhomogeneous. As a result, it is non representative of the interference in the test cell. Estimates of the covariance matrix from nonhomogeneous training data result in severely undernulled clutter. Consequently, CFAR and detection performance suffer. Significant performance improvement can be achieved by employing pre-processing to select representative training data.

The problem of target detection using improved training strategies has been considered in [1–8]. The impact of nonhomogeneity on STAP performance is considered in [8–11]. The works of [1–4, 8, 12] have addressed the use of the non-homogeneity detector (NHD) based on the generalized inner product (GIP) measure for STAP problems involving Gaussian interference scenarios. This work was extended significantly in [13, 14] to include the effects of finite sample support used for covariance matrix estimation. However, the corresponding problem for non-Gaussian interference scenarios has received limited attention.

In this paper, we derive the NHD for non-Gaussian interference scenarios, which can be modeled by spherically invariant random processes (SIRP) and present a statistical analysis of the resultant NHD test statistic. In general, the problem of non-homogeneity



detection for SIRPs is quite difficult due to the fact that the underlying SIRP covariance matrix and characteristic PDF are unknown. For convenience, knowledge of the SIRP characteristic PDF is assumed in this paper.

## 3.2 Preliminaries

Let  $\mathbf{x} = [x_1 \ x_2 \ \dots x_M]^T$  denote a complex spherically invariant random vector (SIRV) having zero mean, positive definite Hermitian covariance matrix  $\mathbf{R}$  and characteristic PDF  $f_V(v)$ . The PDF of  $\mathbf{x}$  is given by [15]

$$f(\mathbf{x}) = \pi^{-M} |\mathbf{R}|^{-1} h_{2M}(q) \quad (3.1)$$

where  $|\cdot|$  denotes determinant and

$$q = \mathbf{x}^H \mathbf{R}^{-1} \mathbf{x} \quad (3.2)$$

$$h_{2M}(w) = \int_0^\infty v^{-2M} \exp(-\frac{w}{v^2}) f_V(v) dv.$$

Every SIRV admits a representation of the form [16]  $\mathbf{x} = \mathbf{z}V$ , where  $\mathbf{z}$  has a complex-Gaussian PDF,  $CN(0, \mathbf{R})$ , and  $V$  is a statistically independent random variable with PDF  $f_V(v)$ . In practice,  $\mathbf{R}$  and  $f_V(v)$  are unknown. For the purpose of this paper, we assume knowledge of  $f_V(v)$  and treat the problem of non-homogeneity detection with respect to unknown  $\mathbf{R}$ .

Previous work [1–4, 8, 12–14] employed the GIP based NHD for Gaussian interference scenarios. However, the GIP based method relying on the statistics of  $Q = \mathbf{x}^H \hat{\mathbf{R}}^{-1} \mathbf{x}$  is unsuitable for SIRV interference scenarios. This is due to the fact that the covariance matrix estimate for this problem can be obtained to within a constant of the covariance matrix underlying the Gaussian component of the SIRV. Typically, this constant is unknown in practice. Consequently, the PDF of  $Q$ , its moments, and the threshold setting for the goodness-of-fit test proposed in [13] cannot be determined. Consequently, we seek a test statistic, which is invariant to the unknown scaling.

## 3.3 Nonhomogeneity Detector for Non-Gaussian Interference Scenarios

Let  $\mathbf{x} \sim SIRV[0, \mathbf{R}_T, f_V(v)]$  denote the complex SIRV test data vector, where  $\mathbf{R}_T$  is unknown. Further,  $\mathbf{x}_i, i = 1, 2, \dots K \sim SIRV[0, \mathbf{R}_T, f_V(v)]$  denote iid target free training data. For homogeneous training data,  $\mathbf{R}_T = \mathbf{R}_x = \mathbf{R}$ . The first step in deriving the NHD detector for SIRVs involves obtaining the maximum likelihood estimate of the underlying covariance matrix. This estimate is then used in a test statistic which exhibits maximal invariance with respect to the unknown scaling of the estimated covariance matrix. The resulting test statistic takes the form of a normalized adaptive matched filter (NAMF), which has been extensively analyzed in [17, 18] and references therein.

### 3.3.1 Covariance Matrix Estimation

The unknown covariance matrix is estimated from target free training data consisting of independent identically distributed SIRVs sharing the covariance matrix of the noise in the test cell. Maximum likelihood (ML) estimation of the covariance matrix for SIRVs was first considered in [19]. The work of [19] showed that covariance matrix estimation for SIRVs can be treated in the framework of a complete-incomplete data problem and pointed out that the maximum likelihood estimate of the covariance matrix is a weighted sample matrix. Since the problem does not permit a closed form solution, [19,20] uses an iterative method known as the expectation-maximization (EM) algorithm. More precisely, let  $\mathbf{x}_i$ ,  $i = 1, 2, \dots, K$  denote independent identically distributed training data sharing the covariance matrix of the test data vector  $\mathbf{x}$ . The work of [19,20] shows that the ML estimate of the covariance matrix is given by

$$\hat{\mathbf{R}} = \frac{1}{K} \sum_{i=1}^K c_i \mathbf{x}_i \mathbf{x}_i^H \quad (3.3)$$

where

$$c_i = -\frac{h'_{2M}(q_i)}{h_{2M}(q_i)} \quad (3.4)$$

$$h'_{2M}(w) = \frac{\partial h_{2M}(w)}{\partial w} = -h_{2M+2}(w)$$

and  $q_i = \mathbf{x}_i^H \hat{\mathbf{R}}^{-1} \mathbf{x}_i$ ,  $i = 1, 2, \dots, K$ . Clearly the transcendental nature of the estimate precludes obtaining a closed form solution. Consequently, [19] used the EM algorithm to obtain an iterative solution to the problem. We adopt the approach of [19] for obtaining the covariance matrix estimate in this work. It can be readily shown that the EM algorithm at convergence produces an estimate which is to within a multiplicative constant of the covariance matrix estimate of the Gaussian component underlying the SIRV. Details pertaining to the initial start and convergence properties of the EM algorithm can be found in [19]. The next step is to use this estimate in a maximally invariant decision statistic for non-homogeneity detection.

### 3.3.2 Maximally Invariant NHD Test Statistic

The maximal invariant statistic for different scaling of test and training data is given by [17]

$$\Lambda_{NAMF} = \frac{|\mathbf{s}^H \hat{\mathbf{R}}^{-1} \mathbf{x}|^2}{[\mathbf{s}^H \hat{\mathbf{R}}^{-1} \mathbf{s}][\mathbf{x}^H \hat{\mathbf{R}}^{-1} \mathbf{x}]} \quad (3.5)$$

where  $\mathbf{s} = \frac{1}{\sqrt{M}}[1 \ 1 \ \dots 1]^T$ . Invariance properties of the test statistic of eq (3.5) and its geometrical representation have been studied in [17] and references therein for the case of Gaussian interference statistics using a sample covariance matrix estimate. In SIRP interference, however, each training data vector realization is scaled by a different realization of  $V$ . Consequently, maximal invariance of the test statistic of eq (3.5) afforded by the sample covariance matrix estimate no longer applies. This is due to the fact that the

sample covariance matrix is no longer the maximum likelihood estimate of the covariance matrix for SIRV scenarios. However, using an estimated covariance matrix of the form of eq (3.3) restores the maximal invariance property of the test statistic of eq (3.5). This is due to the fact that the resultant covariance matrix estimate is to within a multiplicative constant of the covariance matrix corresponding to the Gaussian component of the SIRV.

### 3.3.3 PDF and Moments of the Non-Gaussian NHD Test Statistic

The PDF and moments of the NHD test statistic are readily determined in terms of the corresponding quantities of an equivalent random variable defined by

$$\Lambda_{eq} = \frac{\Lambda_{NAMF}}{1 - \Lambda_{NAMF}} \quad (3.6)$$

It has been shown in [17, 21, 22] that  $\Lambda_{eq}$  admits a representation as the ratio of an F-distributed random variable and a beta-distributed loss factor. In this effort, we are interested in the PDF of  $\Lambda_{NAMF}$  under the condition where no target is present in the test data vector  $\mathbf{x}$ . Specifically, it can be shown from the work of [17, 21, 22] that the PDF of  $\Lambda_{NAMF}$  is given by

$$f_{\Lambda_{NAMF}}(r) = \int_0^1 \frac{L(1-\gamma)f_{\Gamma}(\gamma)(1-r)^{L-1}d\gamma}{[1-(1-\gamma)r]^{L+1}} \quad (3.7)$$

where  $L = K - M + 1$  and  $\Gamma$  is the loss factor random variable, whose PDF is given by

$$f_{\Gamma}(\gamma) = \frac{1}{\beta(L+1, M-1)} \gamma^L (1-\gamma)^{M-2}. \quad (3.8)$$

The mean of  $\Lambda_{NAMF}$  is somewhat difficult to calculate. Consequently, we work with the mean of  $\Lambda_{eq}$  given by

$$E(\Lambda_{eq}) = \frac{K}{(K-M)(M-2)}. \quad (3.9)$$

The statistical equivalence of  $\Lambda_{eq}$  to within a scalar of the ratio of a F-distributed random variable and a beta-distributed loss factor in that it permits rapid calculation of the moments of  $\Lambda_{eq}$ . More importantly, it is extremely useful in Monte-Carlo studies involving simulation of  $\Lambda_{NAMF}$ . For homogeneous training data, the use of (3.6) circumvents the need to explicitly generate the test data vector  $\mathbf{x}$  and the training data vectors used for covariance estimation. For large  $M$  and perforce  $K$ , significant computational savings can be realized from the method of (3.6). It is instructive to note that the PDF of  $\Lambda_{NAMF}$  as well as its mean depend only on  $M$  and  $K$ , which are under the control of a system designer, and not on nuisance parameters such as the true covariance matrix underlying the interference scenario. Furthermore, for  $K \rightarrow \infty$  the mean of eq (3.9) converges to

$$E(\Lambda_{eq}) = \frac{1}{(M-2)}, \text{ corresponding to the mean of an F-distributed random variable.}$$

### 3.3.4 Goodness-of-Fit Tests

Since the PDF and mean of  $\Lambda_{NAMF}$  are known, a formal goodness of fit test can be used for non-homogeneity detection in non-Gaussian interference scenarios. In particular, we form empirical realizations of  $\Lambda_{NAMF}$  from each training data realization using a moving window approach. In this approach each training data vector is treated as a test cell data vector, whose covariance matrix is estimated from neighboring cell data according to eq (3.3). We then test for statistical consistency of these realizations of  $\Lambda_{NAMF}$  with the PDF of eq (3.7). For this purpose a convenient type-I error (typically between 0.01 and 0.1) given by

$$P_e = \int_0^1 \frac{f_{\Gamma}(\gamma)}{[1 + (1 - \gamma)\eta]^L} d\gamma \quad (3.10)$$

is chosen. The threshold,  $\eta$ , is determined by a numerical inversion of eq (3.10). Realizations of  $\Lambda_{NAMF}$ , which exceed  $\eta$  correspond to nonhomogeneous training data. A second test for training data nonhomogeneity is based on comparing each realization of  $\Lambda_{eq}$  with its theoretically predicted mean given by eq (3.9) and retaining those realizations which exhibit the least deviation. Performance analysis of these NHD methods is presented in the next section.

## 3.4 Performance Analysis

Performance of the goodness-of-fit test with simulated and measured data is presented here. Figure 1 shows the plot of the PDF of  $\Lambda_{NAMF}$  with  $K$  as a parameter. Observe that the variance of  $\Lambda_{NAMF}$  decreases with increasing  $K$ . Figure 2 shows a plot of the Type-I error versus the threshold,  $\eta$ , with  $K$  as a parameter. For a given type-I error, the threshold decreases with increasing  $K$ , in conformance with the results of Figure 1. Figure 3 shows the performance of the goodness-of-fit test for simulated homogeneous data from the  $K$ -distribution [15] with shape parameter 0.5 using the covariance estimate of eq (3.3). The results reveal the lack of nonhomogeneity in that no realization of  $\Lambda_{NAMF}$  exceeds the threshold. Figure 4 shows the performance of the goodness-of-fit test in non-homogeneous  $K$ -distributed clutter with shape parameter 0.5. Nonhomogeneity of the data is evident in those range bins where  $\Lambda_{NAMF}$  exceeds  $\eta$ . Figure 5 shows the results of the goodness of fit test for the MCARM data [23] using acquisition 220 on Flight 5, cycle e for 8 channels and 16 pulses. The NHD test statistic,  $\Lambda_{NAMF}$ , and the threshold,  $\eta$ , are plotted as a function of range. Statistical analysis of the data indicates that the data is well approximated by the Gaussian distribution. This fact considerably simplifies the analysis in that the covariance matrix estimate is simply the sample covariance matrix. Non-homogeneity of the training data is evident in those bins for which  $\Lambda_{NHD}$  exceeds  $\eta$ . Figure 6 shows the results from the selection procedure based on comparing the empirically formed  $\Lambda_{eq}$  with its theoretically predicted mean given by eq (3.9). The data set used for this example is identical to the data used in Figure 5. Relevant test parameters are reported in the plot. We observe a significant increase in the number of deviations from the theoretically

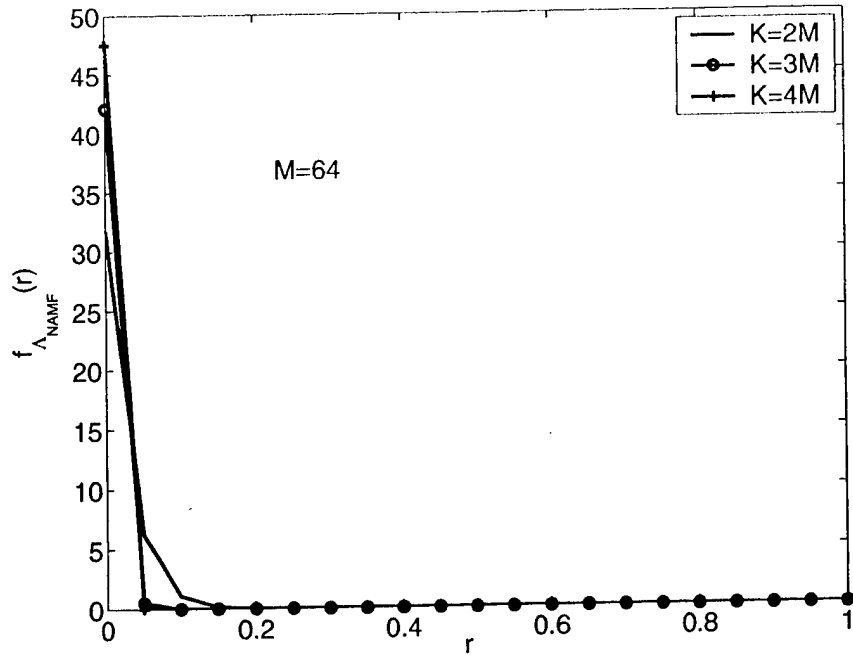


Figure 3.1: NHD Test Statistic PDF

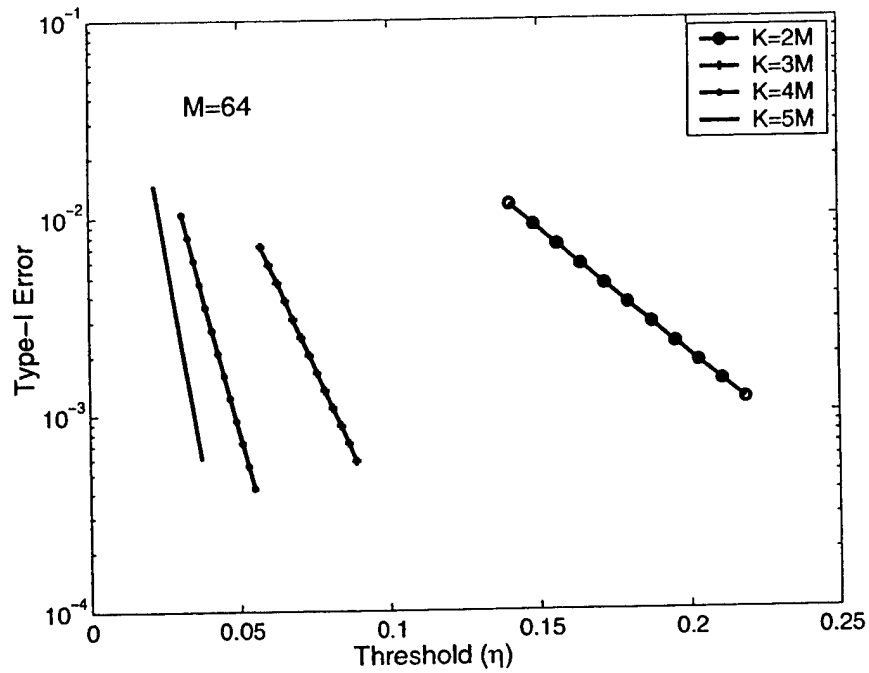


Figure 3.2: Type-I Error vs Threshold for NHD Test Statistic

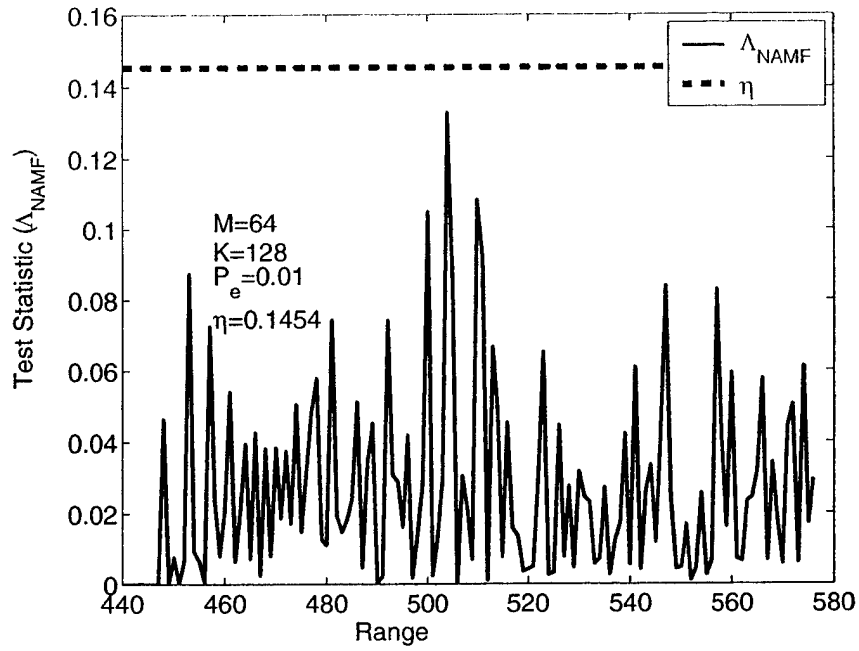


Figure 3.3: Type-I Error vs Threshold for NHD Test Statistic

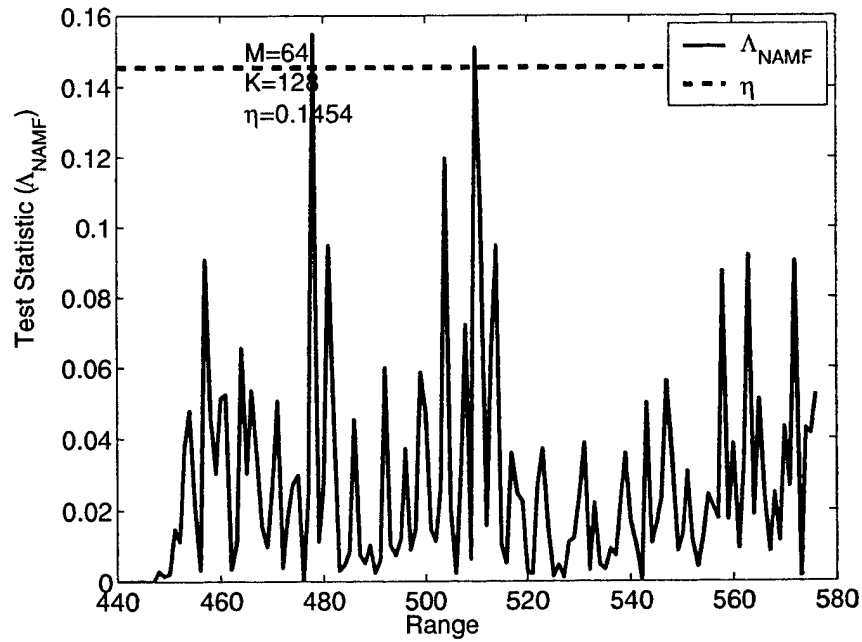


Figure 3.4: Type-I Error vs Threshold for NHD Test Statistic

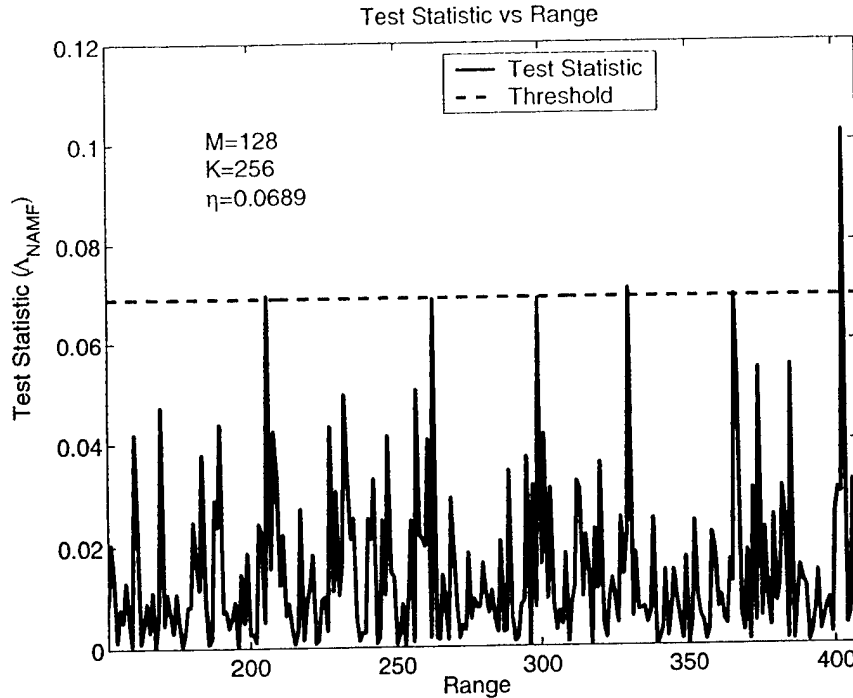


Figure 3.5: NHD Test Statistic vs Range

predicted mean given by eq (3.9). This is due to the fact that we are dealing with a limited number of realizations of the NHD test statistic.

### 3.5 Conclusion

This paper provides a rigorous statistical characterization of the NHD for non-Gaussian interference scenarios which can be modeled as a spherically invariant random process. It is noted that the NHD statistic admits a simple representation in terms of a ratio of an F distributed random variable and a beta distributed loss factor. A formal goodness-of-fit test based on this representation, which follows a randomized F-distribution, is derived. Performance analysis of the method is considered in some detail using measured data from the MCARM program. The illustrative examples validate the approach taken and confirm the results. Future work would include extensive performance analysis using simulated and measured data showing the resulting impact on STAP performance. The performance of several STAP algorithms in Gaussian and non-Gaussian interference scenarios has been considered in [18]. Future work will address performance of the methods treated in [18] with suitable NHD pre-processing.

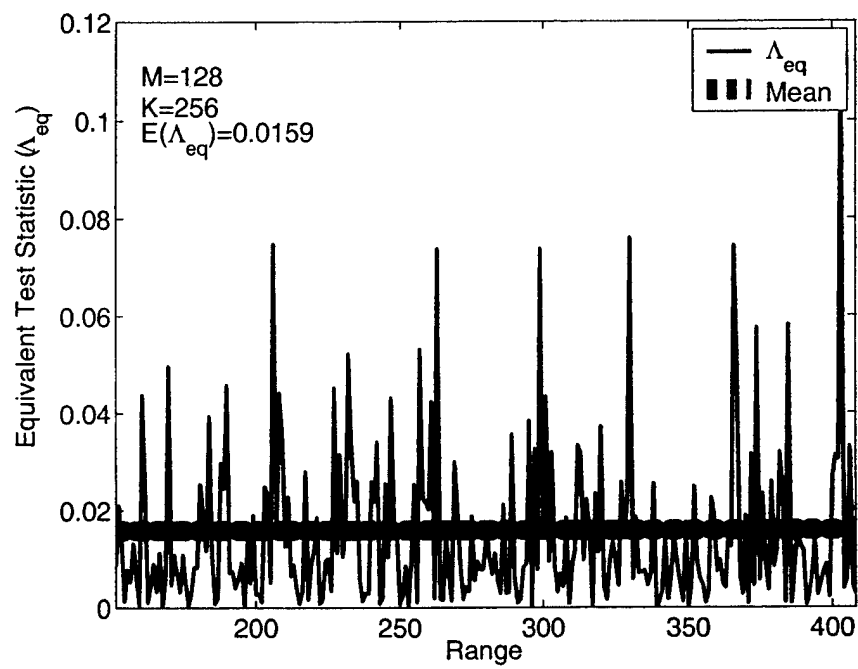


Figure 3.6: NHD Test Statistic vs Range



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